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Review

Empowering Smart Soybean Farming with Deep Learning: Progress, Challenges, and Future Perspectives

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Abstract

This review comprehensively examines the application of deep learning technologies across the entire soybean production chain, encompassing areas such as disease and pest identification, weed detection, crop phenotype recognition, yield prediction, and intelligent operations. By systematically analyzing mainstream deep learning models, optimization strategies (e.g., model lightweighting, transfer learning), and sensor data fusion techniques, the review identifies their roles and performances in complex agricultural environments. It also highlights key challenges including data quality limitations, difficulties in real-world deployment, and the lack of standardized evaluation benchmarks. In response, promising directions such as reinforcement learning, self-supervised learning, interpretable AI, and multi-source data fusion are proposed. Specifically for soybean automation, future advancements are expected in areas such as high-precision disease and weed localization, real-time decision-making for variable-rate spraying and harvesting, and the integration of deep learning with robotics and edge computing to enable autonomous field operations. This review provides valuable insights and future prospects for promoting intelligent, efficient, and sustainable development in soybean production through deep learning.

Keywords: soybean; smart agriculture; sustainable agriculture; crop monitoring and management; precision agriculture; pest and disease control

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1. Introduction

Soybean is one of the world's primary sources of vegetable oil [1]. It possesses high nutritional value, being rich in protein and essential micronutrients beneficial to human health, such as potassium, magnesium, iron, and vitamins B and E. The unsaturated fatty acids present in soybeans also contribute positively to cardiovascular health [2], making soybean-derived products a common component of daily diets worldwide [3]. Beyond its nutritional merits, soybean serves diverse industrial purposes, including the production

of hydraulic oil, plastics, and adhesives [4]. Moreover, it is regarded as a natural "gene reservoir," playing a vital role in crop improvement [5]. Over the past few decades, global soybean production and demand have continued to rise steadily [6], and its applications have expanded across various fields, as illustrated in Figure 1.

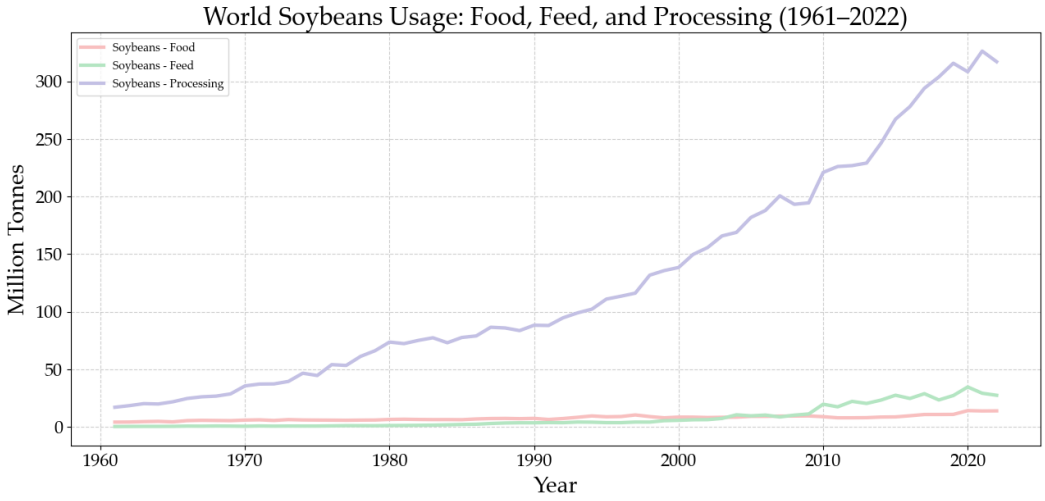


Figure 1. World Soybeans Usage: Food, Feed, and Processing (1961–2022). [Source: https://ourworldindata.org/grapher/soybean-production-and-use, Last Accessed on 29 May 2025].

As illustrated in Figure 1, global soybean consumption has surged from less than 50 million tonnes in 1961 to over 350 million tonnes in 2023—an increase of more than sevenfold. During this period, the composition of soybean usage has undergone a marked transformation. Processing applications (including animal feed, vegetable oil, and biofuel) have become the dominant use, accounting for approximately 75% of total consumption in 2023. Although the share of direct soybean consumption as food has declined, processing applications—including vegetable oil and animal feed production—ultimately support human and animal nutrition, thus remaining a key component of global soybean consumption. In contrast, the share of soybeans consumed directly as food for human consumption (e.g., tofu, soy milk) has declined to below 10%, and the proportion used directly as animal feed has also decreased. Since 2000, driven by biofuel policies and rapidly rising demand for meat in emerging markets, soybean processing has accelerated significantly.

With the continuous growth of the global population, agriculture faces mounting pressure to meet the rising demand for food production [7]. As a major cash crop, soybean is experiencing increasing market demand. Despite the rising dominance of industrial processing applications, soybeans continue to play a fundamental role in global food and feed systems. However, its yield potential is severely constrained by a range of biotic and abiotic factors. Among these, pests and diseases pose significant threats to soybean production in key growing regions [8,9]. To combat these challenges, significant efforts have been made in breeding disease-resistant and stress-tolerant soybean varieties, which have shown promising results in maintaining yield stability. In parallel, soybean has also become a key target crop in the advancement of precision agriculture technologies. Common diseases such as *Sclerotinia* stem rot, *Phytophthora* root rot, and soybean cyst nematode [10], along with newly emerging conditions like the stay-green syndrome [11], have been reported. In addition, insect vectors, such as soybean aphids and thrips, continue to spread these pathogens and disrupt production [12–14]. Abiotic stresses also play a critical role. Low temperatures can delay germination and reduce yields, while high temperatures may impair pollen viability, decrease pod set, and deteriorate grain quality, thus necessitating precise temperature regulation [15]. Drought stress reduces soybean

antioxidant capacity, increases membrane lipid peroxidation, disrupts osmotic regulation, and ultimately hinders plant growth and yield formation [16]. Photoperiod is another influential factor, as soybean is a short-day plant and prolonged daylight delays flowering [17]. Nutrient management further complicates cultivation: excessive nitrogen application can inhibit nodule nitrogen fixation, phosphorus deficiency can directly reduce yields, and over-fertilization may lead to soil compaction [18]. Given these complex challenges, the adoption of advanced technologies is urgently needed to enhance soybean management efficiency and yield performance.

In recent years, the application of deep learning in agriculture has advanced rapidly, giving rise to a series of innovative breakthroughs. Compared with traditional machine learning methods, deep learning offers notable advantages [19–21]. Its ability to automatically extract features enables more accurate identification of crop images, while its end-to-end learning architecture facilitates hierarchical feature learning without relying heavily on manual feature engineering [22–25]. Moreover, techniques such as data augmentation help mitigate the impact of noise commonly present in agricultural datasets, thereby enhancing model robustness [26,27]. The adoption of transfer learning, particularly the use of pretrained models, has further enabled deep learning to maintain strong performance even with limited data, a scenario in which conventional approaches often struggle to generalize or adapt to the complex and dynamic nature of agricultural environments [28,29]. Importantly, deep learning has not only made significant progress in agriculture but has also achieved widespread success in remote sensing and other fields [30–32]. These cross-domain advancements provide a solid technological foundation for its continued development in agriculture. As a result, deep learning is expected to play a central role in driving the future of agriculture toward greater intelligence and precision.

In summary, soybean occupies a pivotal role in the global agricultural system. However, its production is frequently challenged by a range of biotic and abiotic stressors. In recent years, the widespread adoption of deep learning in agriculture has introduced novel solutions to address these complex issues. Leveraging deep learning to enable intelligent optimization across key stages of soybean production has emerged as a critical pathway toward agricultural modernization. To systematically review the research progress and technical landscape in this domain, the structure of this paper is arranged as follows: Section 2 illustrates the literature search and selection strategy based on PRISMA. Section 3 presents an overview of the soybean industry chain and analyzes the core demands driving its transition toward intelligent systems. Section 4 details the applications of deep learning in the soybean domain, focusing on three key areas: pest and disease diagnosis, growth status monitoring and phenotypic analysis, and weed detection and management. Section 5 examines the mainstream deep learning models used in soybean production, explores current model optimization strategies, and evaluates their adaptability across various application scenarios. Section 6 discusses the practical challenges facing current technologies and outlines potential future research directions and development trends. Section 7 concludes the paper with a summary and outlook, aiming to provide theoretical insights and technical guidance for subsequent studies in this field.

2. Literature Search and Selection Strategy Based on PRISMA

This review follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology to ensure transparency and reproducibility in the literature selection process. A comprehensive search was conducted in four major scientific databases: Web of Science, Scopus, IEEE Xplore, and ScienceDirect. The search covered

publications from 2010 to July 2025 and used combinations of keywords such as "soybean," "deep learning," "CNN," "phenotyping," "weed detection," and "precision agriculture."

Studies were included if they met the following criteria: (1) focused on the application of deep learning in any stage of soybean production; (2) peer-reviewed articles written in English; (3) provided technical details on models and datasets used. Exclusion criteria included the following: (1) non-English articles, (2) reviews unrelated to soybean or deep learning, and (3) conference abstracts without full texts.

A total of 1032 records were initially identified through four major databases. After removing 216 duplicates, 816 unique articles remained. Titles and abstracts of these 816 records were screened, resulting in the exclusion of 542 irrelevant or ineligible studies. The full texts of the remaining 274 articles were assessed for eligibility, and 76 were excluded due to reasons such as methodological insufficiency or lack of relevance to soybean deep learning applications. Ultimately, 156 studies were included in the final synthesis. The entire selection process is illustrated in Figure 2 following the PRISMA flow diagram.

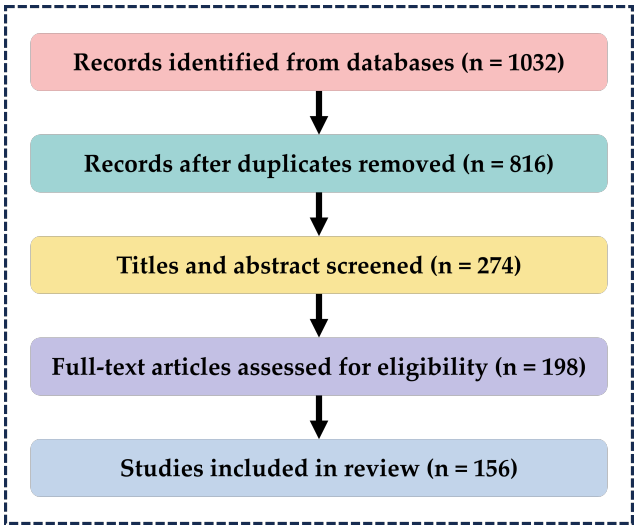


Figure 2. PRISMA flow diagram.

3. Soybean Industry Chain and the Demand for Intelligent Development

The cultivation of soybean dates back to the earliest stages of Chinese agricultural civilization [33]. In response to growing global demands for increased agricultural productivity, all segments of the soybean industry chain are becoming increasingly reliant on intelligent technologies. As a complex system composed of interrelated stages—namely sowing, cultivation, field management, harvesting, and processing—each phase significantly influences the final yield and quality of soybeans.

The sowing stage marks the starting point of the soybean production cycle and serves as the foundation for subsequent growth and output. Optimizing sowing time is critical; early sowing may reduce plant density, whereas delayed sowing can increase protein content but potentially reduce yield. Regional variations in optimal sowing periods are largely governed by environmental conditions [34]. In seed selection, recent studies have explored the use of deep learning for more precise classification. For example, Huang et al. [35] proposed a lightweight deep learning method (SNet) that integrates Mask R-CNN with a mixed feature recalibration module to extract key features of healthy seeds effectively.

The cultivation stage is crucial for ensuring healthy crop growth. Deep learning models, such as CNNs and LSTMs, have been widely adopted to analyze multi-source data, including soil moisture and satellite meteorological images, to facilitate intelligent

irrigation and variable-rate fertilization decisions [36]. Chandel et al. [37], for instance, found GoogLeNet to outperform other models in detecting water stress in soybean crops.

The field management stage is the longest and most technically complex part of the production cycle. The integration of deep learning with UAV technology has significantly improved the identification of pests and diseases in soybean fields, thereby reducing manual labor [38]. Lightweight CNN models have also been employed in weed detection systems to enable precision weeding [39]. Despite achieving high accuracy in disease recognition, weed detection, and yield prediction, current research still faces challenges such as limited data diversity and constrained model generalizability [40].

The harvesting stage is pivotal in determining the final output. Deep learning shows promising potential in maturity detection. For example, Zhang et al. [41] developed DS-SoybeanNet, which combines UAV remote sensing and deep learning, outperforming traditional machine learning in detection accuracy. Recent studies have also explored the integration of deep learning into robotic harvesting systems, using multiple sensors (such as monocular RGB cameras, LiDAR, and thermal imagers) to enhance precision and adaptability [42].

In the processing stage, deep learning surpasses traditional machine learning by automatically extracting complex features (e.g., texture, color, shape) from large-scale image or audio data without manual intervention [27,43]. Zhu et al. [44], for example, proposed a deep learning-based quantitative prediction model to assess soybean processing potential for soy milk, enabling intelligent evaluation and value enhancement of agricultural products.

At a broader level, smart agriculture aims to simulate human cognition and decision-making using artificial intelligence technologies such as deep learning to address complex agricultural challenges [45]. The core demands of intelligent agriculture can be summarized into three dimensions: high throughput, automation, and precision decision-making.

- High-throughput agriculture relies on high-throughput phenotyping platforms that integrate multi-source sensors (e.g., UAVs, LiDAR, multispectral imaging) and AI algorithms to automate environmental data acquisition and analysis. Examples include LQ-FieldPheno [46], HT3P [47], and UIISScan 1.1 [48], which have significantly improved the efficiency and precision of crop monitoring.
- Automation seeks to minimize human intervention in agricultural tasks through deep learning-based autonomous systems, thereby reducing labor costs and improving management efficiency and decision accuracy [49].
- Precision decision-making is driven by high-resolution, real-time agricultural data analyzed through advanced deep learning models. Techniques such as convolutional neural networks, combined with IoT, remote sensing, and transfer learning, have been employed to optimize machinery operations and decision-making processes [50,51].

Historically, soybean has been at the forefront of integrating geospatial technologies into crop management. The NAPPFAST (North Carolina State University's Automated Pest and Pathogen Forecasting System) platform was among the first geoweb tools designed for pest and disease monitoring, utilizing GIS-based modeling to provide early warnings and improve decision-making. Furthermore, HYSPLIT (Hybrid Single-Particle Lagrangian Integrated Trajectory) models were successfully employed to simulate the long-distance aerial dispersion of fungal spores attacking soybean fields, offering insights into epidemic spread patterns. These early implementations demonstrated how spatial modeling and environmental forecasting could directly contribute to yield protection and informed field interventions. The integration of such traditional models with modern deep learning frameworks—by fusing weather, spatial, and image data—holds promise for further enhancing predictive accuracy and operational efficiency in soybean production.

In summary, deep learning plays a pivotal role across all stages of soybean production and serves as a fundamental driver of agricultural intelligence. Its advantages lie not only in end-to-end learning capabilities, automatic feature extraction, strong transferability, and robustness, but also in its flexible architectures that can be tailored to a wide range of agricultural tasks. Representative models include stacked autoencoders (SAEs), deep belief networks (DBNs), deep Boltzmann machines (DBMs), convolutional neural networks (CNNs), graph neural networks (GNNs) [52], and generative adversarial networks (GANs) [53]. CNNs excel in pest and disease detection from crop images [54,55]; GNNs are effective in modeling spatial relationships within fields for yield prediction [56]; and GANs show considerable promise in image enhancement and remote sensing data generation [57,58].

4. The Applications of Deep Learning in Soybean Production

4.1. Diagnosis of Soybean Diseases and Pests

Pests and diseases have long been a major constraint on agricultural productivity and crop yield [59]. Traditional manual identification methods are inefficient and prone to errors, often resulting in substantial crop losses. With the rapid advancement of deep learning and its widespread application in image recognition, intelligent detection and monitoring of crop pests and diseases have emerged as a key area of modern agricultural research.

Deep learning offers powerful capabilities in processing image and sensor data, enabling effective integration with agricultural hardware systems. For instance, Park et al. [60] developed a soybean pest detection and forecasting platform based on unmanned ground vehicles (UGVs) and multiple deep learning algorithms (e.g., MRCNN, YOLOv3, Detectron2). Their system enabled early pest monitoring via image recognition and included a lightweight web-based application to support agricultural management. Similarly, Abed et al. [42] employed camera-equipped robots for in-field acquisition of soybean leaf images, which were processed by a U-Net and ResNet34-based segmentation model, followed by classification using DenseNet121 to distinguish healthy and diseased leaves. Nguyen et al. [61] further demonstrated the potential of hyperspectral imaging (400–1000 nm) combined with 2D/3D CNNs to detect grapevine virus infections at asymptomatic stages, offering a non-invasive solution for early disease warning. Notably, Sharma et al. [62] proposed SoyaTrans, a diagnostic model for soybean leaf diseases based on the Swin Transformer architecture integrated with CNN-derived features. The model achieved a 94% accuracy on a custom soybean leaf dataset. Figure 3a illustrates the data collection process, and Figure 3b shows the SoyaTrans architecture.

Fara et al. [63] applied transfer learning using a pretrained VGG19 model optimized with RMSprop to construct a classification network for three types of soybean leaf diseases. Omole et al. [64] utilized VGG16 and VGG19 models to detect soybean diseases and validated the efficacy of CNNs for early diagnosis through k-fold cross-validation and standard preprocessing. Goshika et al. [65] trained a YOLOv5-based model on a large-scale image dataset to classify five severity levels of soybean diseases, achieving a mAP of 92%. Yu et al. [66] introduced a soybean leaf disease identification method using an enhanced Residual Attention Network (RANet) that incorporated OTSU segmentation and data augmentation, reaching an accuracy of 98.49%. Building on this, Yu et al. [67] extended the task to four disease categories, employing stricter data splitting protocols, batch normalization, learning rate decay, and a transfer-learning-enhanced ResNet18 (TRNet18), which improved the accuracy by an additional 1.04%. The final test set accuracies for five models were as follows: AlexNet (76.54%), ResNet18 (98.42%), TRNet18 (99.53%), ResNet50 (95.89%), and TRNet50 (98.42%). Figure 4 illustrates some samples of soybean diseases.

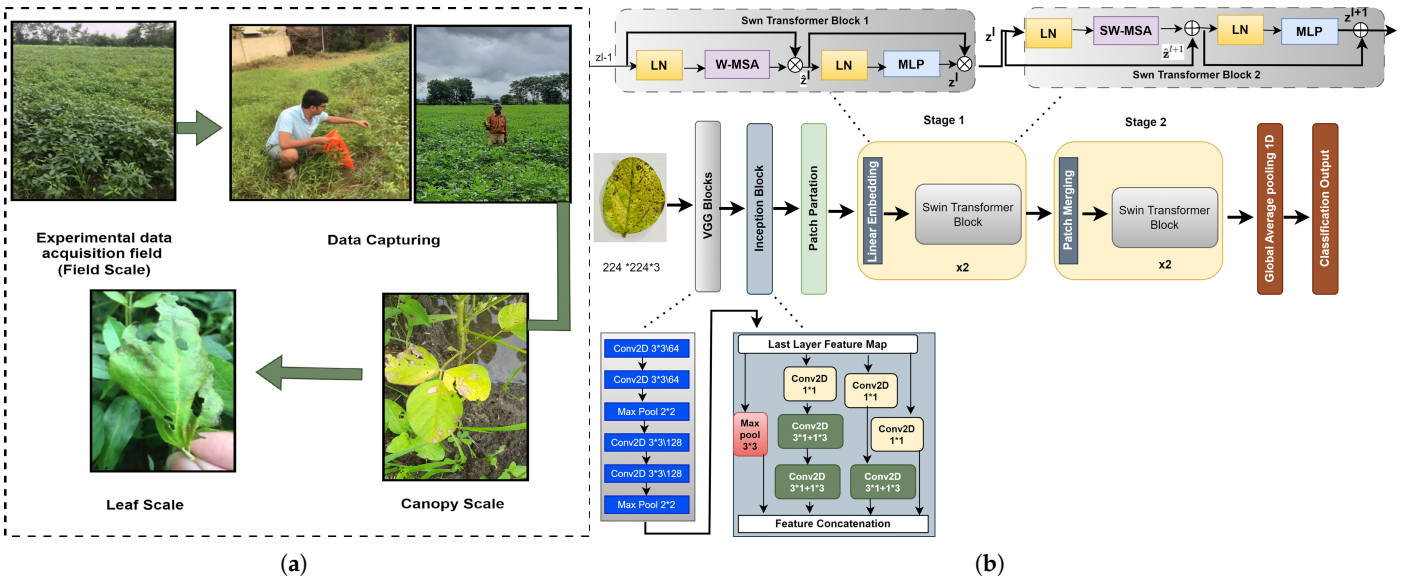


Figure 3. (**a**) Architectural outline of the SoyaTrans model; (**b**) workflow of soybean disease data collection [62].

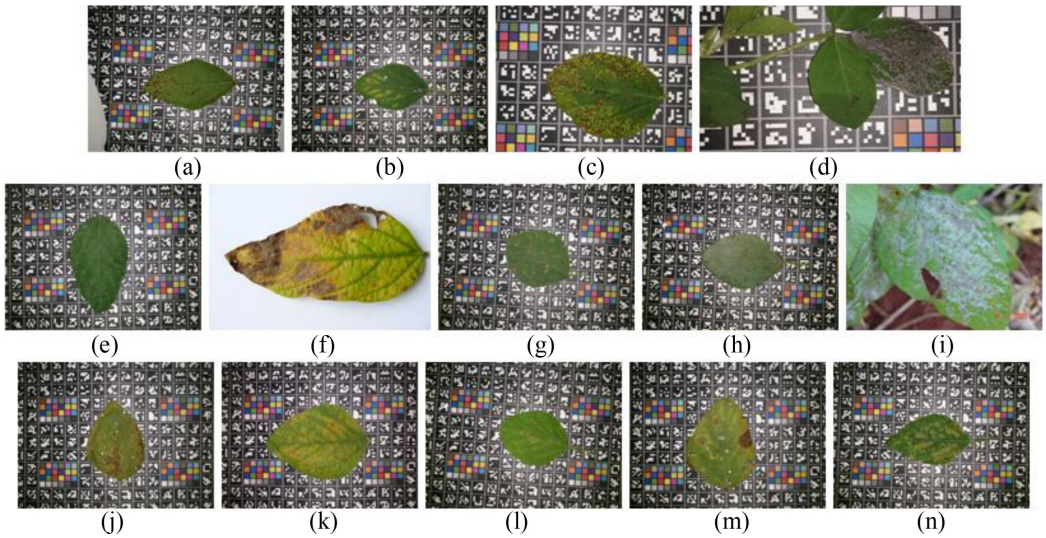


Figure 4. Few sample soybean leaf diseases: (**a**) bacterial blight, (**b**) soybean mosaic virus, (**c**) copper phytotoxicity, (**d**) charcoal rot, (**e**) healthy, (**f**) leaf cercospora, (**g**) downy mildew, (**h**) powdery mildew, (**i**) powdery mildew and rust, (**j**) rust, (**k**) rust and target spot. (**l**) Brown spot, (**m**) southern blight, and (**n**) unknown disease [68].

These findings underscore the growing accuracy of deep learning models in pest and disease identification. However, the pursuit of higher accuracy often results in increasingly complex models with substantial computational demands, hindering practical deployment in agricultural environments. Lightweight models, which reduce parameter counts and computational overhead, offer a promising alternative by lowering storage, computation, and energy requirements—making them well-suited for deployment on resource-constrained edge devices while maintaining high performance [69]. Such solutions are particularly relevant for small-scale farms where cost and energy efficiency are critical, enhancing operational efficiency without compromising diagnostic accuracy.

It is worth noting that open-access datasets specific to soybean pest and disease detection remain scarce. To address this gap, our previous research introduced a general pest and disease classification model called CRE, based on masked image modeling and

contrastive learning. We also constructed a large-scale open-source dataset containing 205,371 images, including 9613 images of soybean-related pests and diseases [9], providing essential data resources for future research in this domain.

According to the studies mentioned above, the primary challenges in current soybean diseases and pests diagnosis research can be summarized as follows:

1. Limited model generalizability, which hampers adaptability to variations in region, climate, and field conditions;
2. Underdeveloped multimodal data fusion frameworks, with an over-reliance on RGB imagery and insufficient integration of hyperspectral, thermal infrared, and environmental sensor data;
3. Lack of open-access, high-quality, and standardized image repositories for soybean pest and disease detection, restricting model reproducibility and comparative evaluation;
4. Unoptimized trade-offs between model deployment and energy consumption, resulting in limited practicality and scalability.

To address these challenges, future research should focus on the following directions:

- Development of multimodal recognition frameworks that integrate RGB, hyperspectral, thermal imaging, and LiDAR data to enhance model adaptability across diverse agricultural scenarios;
- Incorporation of multi-temporal remote sensing and UAV imagery to enable dynamic modeling and early warning of pest and disease progression over time;
- Advancement of lightweight models for edge deployment, tailored to meet the agricultural sector's requirements for low cost, low energy consumption, and minimal latency;
- Construction of standardized and diversified soybean pest and disease image databases to improve model transferability and robustness across different environments;
- Promotion of cross-disciplinary research, such as integrating GANs, digital twins, sim2real transfer, and domain adaptation techniques into agricultural vision tasks, thereby mitigating challenges related to high annotation costs and sample imbalance.

It is worth noting that soybean production occurs across diverse geographic regions with substantial variation in climate, temperature, and precipitation. These environmental differences can significantly affect model performance and generalizability. Some studies have demonstrated that environmental variability—rather than model complexity alone—plays a key role in recognition accuracy. For example, a CNN model trained in temperate zones may perform poorly in tropical climates without domain adaptation.

Moreover, the incorporation of vegetation indices (VIs), such as NDVI, SAVI, and EVI, into deep learning pipelines has shown the potential to enhance pest and disease detection, especially under conditions where RGB imagery lacks a sufficient spectral resolution. However, further research is needed to systematically compare the performance of different VIs in soybean-specific scenarios.

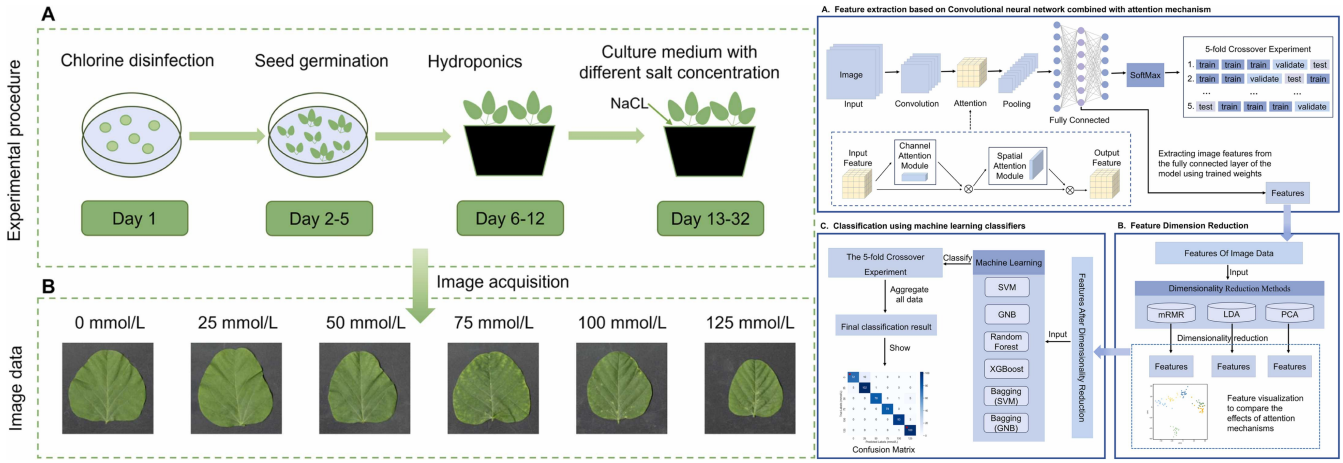
In parallel, recent work has explored the use of hyperspectral and multispectral data to capture crop spectral signatures across growth stages. These spectral features, spanning visible to near-infrared wavelengths, enable more accurate modeling of physiological traits and stress symptoms. Integrating such spectral data with deep learning models could significantly improve early diagnosis and crop health monitoring.

4.2. Soybean Growth Status and Phenotypic Trait Detection

Phenotypic trait detection and growth monitoring in plants heavily rely on image-based analysis to distinguish features and extract key characteristics at the individual plant level [70–73]. In the case of soybean, subtle yet significant variations in morphological structure, textural details, and spectral features arise across different growth stages, health

conditions, and varietal attributes. These variations often pose challenges for traditional image processing methods, which struggle to deliver efficient and precise recognition [74,75]. In contrast, deep learning, with its powerful image analysis capabilities and multi-level feature extraction, has emerged as a crucial technology in soybean phenotyping, providing strong support for breeding, trait improvement, and physiological assessment [76–78].

To enhance physiological state perception, Yang et al. [79] developed a CNN model enhanced with an attention mechanism (AM), coupled with dimensionality reduction (DR) techniques and machine learning classifiers, to classify salt stress levels in soybeans using RGB images. For drought stress detection, Xu et al. [80] proposed MSAFNet, a ResNet50-based architecture integrating squeeze-and-excitation (SE) attention and multi-scale feature fusion modules. This model achieved an accuracy of 90.2% and an F1-score of 91.3% in simulated tests while maintaining a real-time inference speed of 13.6 fps. Figure 5a illustrates the image acquisition process under varying salt stress levels, and Figure 5b presents the MSAFNet model architecture.



(**a**) (**b**)

Figure 5. (**a**) Image acquisition process under varying salt stress levels; (**b**) MSAFNet model architecture [79].

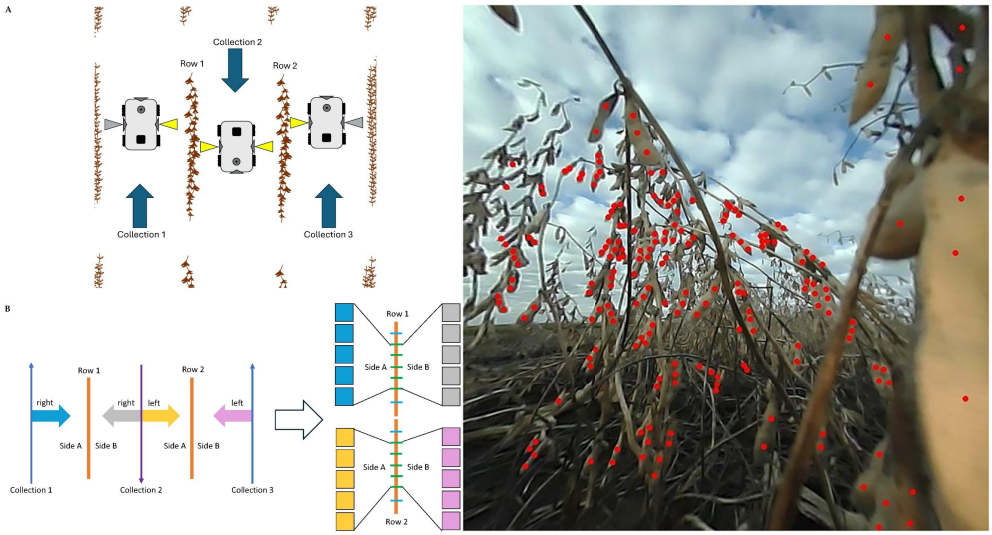
In terms of trait identification, Grinblat et al. [81] used deep convolutional neural networks (DCNNs) to model leaf venation morphology, significantly improving classification accuracy across three legume species and visualizing critical venation features. Wang et al. [82] demonstrated that fusing deep features from upper, middle, and lower leaf images of soybean plants enhances variety classification performance. Lin et al. [83] developed an online seed classification system using multi-scale Retinex segmentation and a lightweight CNN model (SoyNet), effectively improving seed recognition efficiency.

Yield estimation, particularly via counting tasks, has become a focal point in recent research. Li et al. [84] proposed a two-column CNN (TCNN) for accurate soybean pod modeling and seed count estimation, significantly outperforming traditional counting approaches. Zhang et al. [74] built a high-precision phenotypic extraction model based on YOLOv8, achieving pod and seed recognition with an R^2 of 0.96 and RMSE values of 2.89 and 6.90, respectively, laying the groundwork for downstream yield prediction. Liu et al. [85] introduced SmartPod, a Transformer-based model employing semi-supervised learning for field pod counting, attaining an average accuracy of 94.1%. The data collection and annotation process is shown in Figure 6.



Figure 6. Image acquisition and annotation process [85]. (**a**) TraitDiscover high-throughput phenotyping platform; (**b**) example of image annotation.

Additionally, Sun et al. [76] combined UAV-based hyperspectral imaging with a prototype contrastive learning network for soybean yield estimation and lodging classification, boosting accuracy by 48% and demonstrating the potential of remote sensing fused with deep learning in complex agricultural tasks. Feng et al. [86] used a UGV to collect field video data of soybean pods and developed a high-throughput yield prediction system, achieving 83% accuracy while reducing data collection costs by 32% compared to traditional methods. The collection and identification process is illustrated in Figure 7.



(**a**) (**b**)

Figure 7. (**a**) (A) Data collection for a single plot: Yellow-highlighted cameras recorded the center plot; gray ones recorded others. Three passes were required to fully capture one plot. Python scripts automatically organized videos by plot. Arrows indicate robot movement direction; (B) image sampling: Each row was evenly divided into eight sections using seven splitters. Images from the middle five were used (excluding the first and last). The two rows of each plot were combined into one, yielding 10 images per side, 20 per plot; (**b**) results of soybean seeds counting [86].

Despite these advancements, several challenges persist:

1. Limited model generalizability, particularly under complex and dynamic field conditions;
2. Insufficient multimodal fusion, as most current models rely on single-modality inputs (e.g., RGB or hyperspectral images), limiting their ability to leverage diverse sources of information;

3. Scarcity of high-quality, multi-annotated public datasets, which hampers training and benchmarking of models.

Future research should focus on the following key directions:

- Multimodal data fusion: Integrate RGB, hyperspectral, LiDAR, and thermal images to improve model adaptability and robustness in complex field scenarios.
- Multi-temporal remote sensing modeling: Use UAV imagery to dynamically monitor the full soybean growth cycle from sowing to harvest, enabling comprehensive modeling of growth stages, stress responses, and yield fluctuations.
- Lightweight model design and deployment optimization: Develop models suitable for edge computing to ensure efficient deployment in resource-constrained farm environments.
- Construction of standardized large-scale phenotyping databases: Promote the creation of open-access, high-quality soybean image datasets to enhance model comparability and reproducibility.

In summary, deep learning has shown strong potential in tasks such as soybean phenotyping, stress detection, and yield estimation. However, its widespread practical deployment requires further exploration in multimodal integration, deployment feasibility, and data resource development.

4.3. Weed Detection and Management

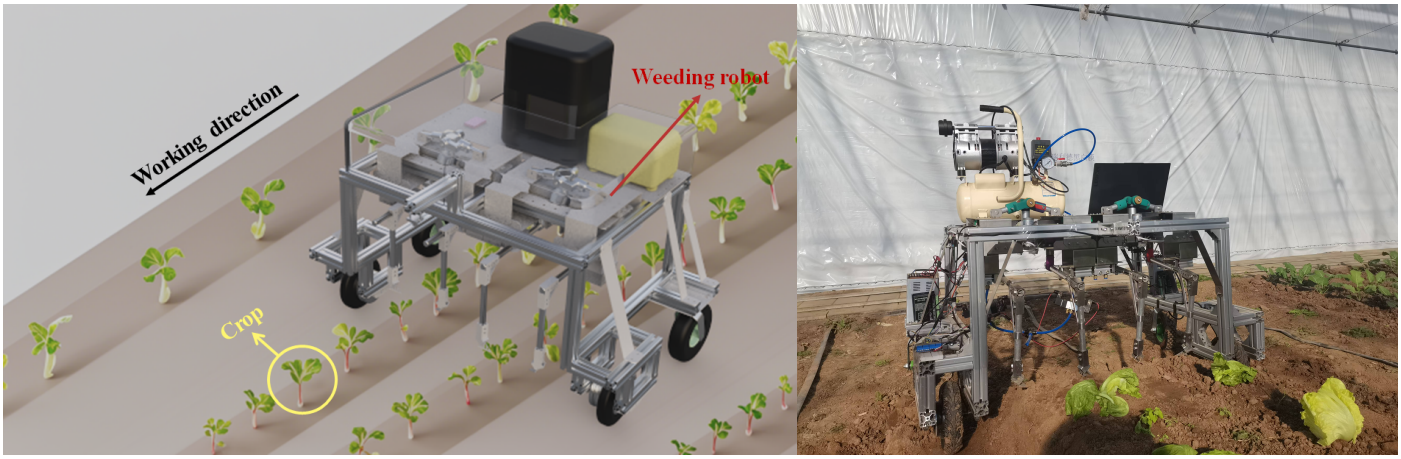
Effective weed management remains a critical factor in ensuring soybean yield and quality in modern agriculture [87]. However, traditional manual weeding methods are labor-intensive, costly, and inadequate for the demands of large-scale cultivation [88]. With the rapid advancement of computer vision and deep learning, numerous intelligent detection and automated weeding solutions have emerged, offering new strategies for soybean field management [23].

In complex and dynamic field environments, accurate detection of soybean plants and their center points is essential. Deep learning models, often combined with crop-specific features, enable precise crop-weed differentiation and provide vital data for path planning and control in automated weeding. For example, Jiang et al. [89] employed fluorescence imaging and multi-view localization to achieve 96.7% accuracy in automatic soybean seedling positioning. Su et al. [90] further integrated fluorescence imaging with 3D plant localization to distinguish between inter-row soybean plants and weeds, reaching 97% accuracy. These high-precision localization techniques provide a foundation for both mechanical and laser-based weeding and support the extraction of accurate navigation lines for UGVs.

Following plant localization, weed detection and classification can be achieved through semantic segmentation, object detection, or multi-task learning frameworks. These methods can distinguish between grass and broadleaf weeds and identify their growth stages [91,92], facilitating stage-specific weeding strategies and tailored herbicide application plans. For instance, early-stage weeds may be best managed through mechanical weeding, while late-stage or spatially dense weed populations can be targeted with precision spraying.

By integrating crop center point data with weed spatial distribution, inter- and intra-row weeding robots can autonomously plan paths and control various weeding actuators. Multiple execution modules—including mechanical, pneumatic, laser, and flame-based tools—can be integrated and deployed based on spatial crop-weed information to achieve high-precision, low-damage field operations. These robots can dynamically adjust the trajectory of weeding arms to avoid soybean plants while maximizing weeding efficiency. In our previous study on lettuce [88], we developed a pneumatic intra-row weeding robot (as shown in Figure 8), whose design and control principles could inform future development of soybean-specific weeding platforms. Additionally, Ye et al. [93] proposed

a resilient comb-type intra-row soybean weeding robot based on PLC and laser ranging sensors (as shown in Figure 9), demonstrating the potential of hardware innovation in real-world applications. However, the system has not yet incorporated deep learning; future iterations could explore advanced models such as Mamba [94] to further enhance task accuracy and decision intelligence.



(**a**) (**b**)

Figure 8. (**a**) Schematic diagram of field operation of weeding robot; (**b**) filed scenario [88].



(**a**) (**b**)

Figure 9. (**a**) Weed control device installation position; (**b**) test scenario [93].

For weed populations requiring chemical treatment, object detection results can be combined with GPS/RTK data to enable geospatially aware path planning and differentiated precision spraying. Such intelligent spraying systems can reduce pesticide use and environmental impact. Meanwhile, visual navigation technologies are vital for maintaining operational continuity and stability. Recent research has integrated visual odometry, inertial navigation units (IMUs), and LiDAR into robotic platforms, alongside deep learning modules for object detection and semantic understanding, enabling autonomous navigation in environments with hills, lodged crops, or discontinuous ridges [95,96]. The application of Simultaneous Localization and Mapping (SLAM) further allows robots to perform mapping and localization simultaneously, significantly improving system flexibility and intelligence [97]. Looking ahead, incorporating Active Disturbance Rejection

Control (ADRC) could enhance path planning and motion control of UGVs or UAVs, offering better stability and precision under complex environmental disturbances [98].

Despite significant progress, several challenges remain:

1. Insufficient real-time multimodal data fusion: Most current systems rely on single-sensor inputs and lack efficient mechanisms for integrating multimodal data, limiting their adaptability to environmental changes.
2. Limited model generalization and deployment adaptability: Deep learning models often struggle to generalize across diverse field conditions, regions, and growth stages due to limited training data and transfer difficulties.
3. Lack of dynamic decision-making in weeding strategies: Many weeding robots still follow preset paths or fixed parameters, lacking the flexibility to adjust strategies based on real-time conditions.
4. Balancing system complexity and economic feasibility: Achieving large-scale deployment requires managing hardware complexity and costs without compromising system performance.

Future research should focus on the following directions:

- Develop lightweight, multi-task learning models optimized for real-time execution on edge devices;
- Introduce self-supervised and reinforcement learning mechanisms to enhance model adaptability in complex environments;
- Build open-access, multimodal field datasets for soybean to support high-quality model training and benchmarking;
- Explore multi-robot cooperative weeding systems, integrating coordination protocols to improve field-level management efficiency;
- Deeply integrate ADRC and deep learning-based navigation systems to construct intelligent platforms with high stability and dynamic control capabilities.

5. Mainstream Models and Optimization Strategies

5.1. Mainstream Models

With the ongoing advancement of computer vision in agriculture, deep learning models have become the core tools for intelligent soybean production. Based on their network architectures and task adaptability, mainstream models can be categorized into four types: image classification models, object detection models, image segmentation models, and Transformer-based models. Each type exhibits distinct characteristics in terms of processing capabilities, deployment flexibility, and fine-grained recognition performance.

First, image classification models are primarily used to determine the overall health status of soybean leaves and identify disease types within a single image [99]. Representative models include ResNet, which employs residual connections to mitigate degradation in deep networks, allowing for deeper architectures with reduced overfitting risk [100,101]; DenseNet, which enhances feature propagation and reuse through dense connections [102,103], has demonstrated strong performance in classifying diverse soybean leaf disease types [104,105]; and EfficientNet, which utilizes compound scaling to achieve high accuracy with significantly fewer parameters and reduced computational cost [106,107], making it particularly suitable for deployment on edge devices and unmanned platforms. However, these models typically require pre-cropped images focused on a single leaf or region and do not provide information on the precise location of lesions within the image [108].

Second, object detection models are designed to simultaneously localize and classify targets within images, playing a crucial role in intelligent field monitoring and precision

spraying. The YOLO (You Only Look Once) family of models, known for their end-to-end structure, fast inference speed, and strong generalization capabilities [88,109–116], are widely used in field-based pest detection. For instance, YOLOv5 enables high-accuracy detection under limited computational resources, while YOLOv8 integrates attention mechanisms to improve the detection of small insects and occluded lesions [110,111,117,118]. In comparison, Faster R-CNN, with its two-stage architecture, achieves a higher detection accuracy [119,120], making it suitable for fine-grained lesion detection in high-resolution images. SSD (Single Shot Detector) [121] offers a balance between speed and accuracy, ideal for medium-scale recognition tasks on vehicle-mounted or UAV platforms.

Third, image segmentation models perform pixel-level delineation of lesion areas and leaf regions, supporting subsequent analyses such as area calculation and severity assessment [70,122]. The widely adopted U-Net architecture [123], originally developed for medical image segmentation, excels in soybean leaf lesion extraction and yield estimation due to its efficiency and strong performance on small datasets [124,125]. Mask R-CNN extends Faster R-CNN with an additional segmentation branch [126], allowing for the simultaneous detection and region delineation of lesions. DeepLabV3+, with atrous convolutions and multi-scale receptive fields, maintains accurate boundary information under complex backgrounds, making it well-suited for large-field disease segmentation tasks [127]. However, segmentation models typically require high-quality annotated data and are computationally intensive, which limits their deployment on low-power devices.

Finally, Transformer-based models have gained prominence in agricultural monitoring and temporal analysis. The Vision Transformer (ViT) divides images into patches and processes them as tokens, enabling effective global modeling for tasks such as analyzing disease progression across soybean growth stages [128,129]. Swin Transformer introduces a shifted window mechanism that balances local and global feature modeling, improving its ability to extract complex visual patterns like lesions and insects [62,130]. DETR, an end-to-end Transformer-based detection framework [131], demonstrates high robustness in localizing pests and diseases in remote sensing imagery. Despite their high performance, Transformer-based models often have large parameter sizes and high computational demands, necessitating further lightweight optimization for practical deployment in agricultural scenarios.

In summary, each model type offers unique advantages and limitations in terms of accuracy, efficiency, and task applicability. Researchers must select appropriate architectures based on specific application contexts. Future research should explore strategies such as model fusion, cross-modal enhancement, and knowledge distillation to develop intelligent recognition systems that balance performance, generalizability, and deployability. Table 1 summarizes the representative models, application tasks, advantages, limitations, and future directions for each of the four model categories.

Table 1. Summary of deep learning model types and their applications in soybean production.

Model Type	Representative Models	Application Tasks	Advantages	Limitations	Future Directions
Image Classification	ResNet, DenseNet, EfficientNet	Disease classification	High accuracy, clear architecture	No lesion localization	Multi-modal and multi-temporal integration
Object Detection	YOLO, Faster R-CNN, SSD	Lesion and pest detection, seed detection, yield estimation	Real-time performance, versatile	Poor performance on small targets	Multi-scale detection, small object enhancement
Image Segmentation	U-Net, Mask R-CNN, DeepLabV3+	Lesion segmentation	Pixel-level output	Labeling-intensive, high resource demand	Lightweight architectures, self-supervised learning
Transformer-Based	ViT, Swin Transformer, DETR	Remote sensing, dynamic modeling	Strong global modeling capability	High computational cost	Multi-modal fusion, lightweight optimization

5.2. Lightweight Architectures, Transfer Learning, and Model Optimization Strategies

To address challenges such as limited computational resources, insufficient annotated data, and complex deployment environments across the soybean industry chain, researchers have proposed a variety of model architecture and training strategy optimizations [132,133]. This section outlines five representative optimization approaches and illustrates their typical applications throughout different stages of soybean production.

Lightweight Model Design: Lightweight architectures are a key solution for overcoming deployment constraints on agricultural edge devices. In tasks such as sowing monitoring, emergence evaluation, and in-field seedling inspection, computational platforms are often vehicle-mounted cameras, low-power embedded boards, or autonomous mobile units. Models such as MobileNet [134], the MobileViT series [135–137], and EfficientNet-lite [106] significantly reduce model complexity through techniques like depthwise separable convolutions, group convolutions, and channel pruning. These models enable real-time detection of emergence density, missing seedlings, and seeding uniformity. In harvesting scenarios, lightweight structures can also be embedded into combine harvester vision systems to simultaneously perform pod counting and plant localization, thereby enhancing operational efficiency.

Transfer Learning: Transfer learning [138] has been widely adopted across the soybean industry, particularly in scenarios with limited data or high labeling costs. For instance, during the early growth stage, pretrained models such as ResNet or ViT can be fine-tuned to transfer knowledge from other crops (e.g., cotton) or simulated environments to soybean leaf classification tasks [139], reducing the need for extensive image acquisition. In pod maturity recognition or leaf nutrient diagnosis, transfer learning allows models to achieve acceptable accuracy using only a small number of field-annotated samples, effectively addressing cross-region and cross-variety adaptability issues in agronomic research.

Self- and Semi-Supervised Learning: These learning paradigms offer promising alternatives for addressing label scarcity in field data. Traditional supervised learning struggles to exploit the full potential of unlabeled images. Self-supervised methods such as SimCLR [140], MoCo [141], and MAE [142] can be used to pretrain models on reconstruction or contrastive tasks in applications like sowing zone monitoring or early-stage field variation analysis. When combined with semi-supervised strategies, models can leverage pseudo-labeling to enhance early-stage pest and disease recognition—especially beneficial for emerging diseases or rare soybean cultivars with limited training data.

Model Compression and Deployment Optimization: Compression techniques have broadened the applicability of deep models in real-time tasks such as harvest control and autonomous field inspections. Methods including pruning, quantization, and knowledge distillation enable the compression of large models (e.g., YOLO, ViT, DeepLab) into versions suitable for ARM processors, FPGAs, or edge GPUs. For example, in pod density estimation and harvesting decision-making, quantized YOLOv5 models can be embedded into harvest control systems to achieve low-latency, closed-loop operations encompassing image recognition, motion planning, and control execution—significantly improving precision and responsiveness in automated harvesting equipment.

Multimodal Fusion and Fine-Grained Detection: This is an increasingly important direction for enhancing soybean intelligent recognition systems. Tasks such as quality grading and yield estimation require more than RGB images to accurately reflect intrinsic traits and environmental conditions. Fusing data from infrared imagery, hyperspectral imaging, NDVI vegetation indices, and meteorological sensors allows for deeper model understanding of protein content, pod fullness, and latent diseases. In fine-grained detection tasks—such as identifying early-stage insect pests, soybean inflorescences, or subtle lesion

patterns—modules like FPN [143], CBAM [144], and CoordAtt [145] help models perceive minute features more effectively, improving robustness in complex visual backgrounds.

In summary, optimization strategies centered around lightweight design, transfer learning, self-/semi-supervised training, model compression and deployment, and multimodal fusion have demonstrated practical potential across multiple stages of the soybean production chain. These approaches not only enhance model efficiency and environmental adaptability but also lay a solid foundation for advancing agricultural AI toward "end-to-end coordination, low-cost deployment, and high-precision decision-making."

In addition to remote and UAV-based sensors, field spectroradiometry provides fine-grained, high-resolution spectral data that is particularly valuable for early stress detection and physiological trait estimation in soybean. Instruments such as ASD FieldSpec or other handheld hyperspectral spectrometers can measure reflectance across hundreds of bands, offering rich input features for deep learning models. These datasets have been successfully integrated with CNNs and LSTMs to model nitrogen content, chlorophyll concentration, and drought stress responses at the canopy level. Such field-based data collection bridges the gap between laboratory calibration and large-scale field deployment, improving model robustness and transferability across environmental conditions. Incorporating field spectroradiometry with deep learning represents a promising direction for precision phenotyping in soybean research.

6. Discussion

6.1. Challenges

Despite the considerable potential of deep learning in applications throughout the soybean production phase, from pre-sowing to post-harvest, its real-world implementation still faces several significant challenges.

First, the dual bottleneck of data quality and model generalization continues to hinder performance stability and transferability. Due to the inherent variability of natural agricultural environments, image acquisition is often affected by inconsistent lighting, varying angles, and severe occlusion. Combined with the high cost and low efficiency of manual annotation, these factors have resulted in a scarcity of high-quality soybean datasets for model training. Consequently, models are prone to overfitting in specific scenarios and lack the robustness needed for cross-regional or cross-seasonal deployment [27].

Second, numerous difficulties arise in real-world model deployment. Deep neural networks typically involve large numbers of parameters and high computational complexity, which imposes substantial demands on hardware resources [7]. This is in stark contrast to the resource-constrained conditions of agricultural environments, where edge devices often have limited processing power. In tasks requiring real-time responses—such as weeding and spraying—models often fail to run efficiently on embedded systems, severely limiting their engineering viability.

Moreover, the high complexity of field environments places stringent demands on model perception and robustness. Crops, weeds, and background elements frequently overlap or occlude one another, and natural disturbances are common. As a result, single-modality inputs (e.g., RGB imagery) are often insufficient for robust feature representation [146–148]. Although multimodal sensing technologies have been proposed as potential solutions, practical applications face major challenges, including feature heterogeneity, scale mismatches, and temporal–spatial misalignment between modalities. An efficient and unified multimodal fusion framework remains lacking.

More critically, the field of agricultural artificial intelligence lacks a standardized evaluation system. There are no widely accepted benchmarks for task definitions, dataset construction, or model performance assessment. This absence of common standards

leads to poor comparability between studies, difficulty in reproducing experiments, and significant barriers to engineering translation. The lack of standardized frameworks directly impedes horizontal benchmarking, vertical iteration, and practical adoption—ultimately hindering the establishment of a robust technological development pathway.

6.2. Future Perspectives

To address the aforementioned challenges, advancing the application of deep learning in the soybean industry requires a dual focus on methodological innovation and system-level integration.

First, the incorporation of reinforcement learning and self-supervised learning offers promising solutions to the issues of data scarcity and decision-making complexity in agricultural settings. Reinforcement learning excels at long-term policy optimization, making it suitable for high-level tasks such as machinery path planning and operational decision-making. In contrast, self-supervised learning constructs pretext tasks to uncover latent structural features from large-scale unlabeled datasets, thereby enhancing the model's generalization and representational capabilities without relying on manual annotations.

At the perception layer, multisensor data fusion is key to improving field-level recognition accuracy and environmental adaptability. Integrating RGB imagery, infrared thermography, LiDAR, soil moisture, and meteorological sensor data enables the construction of comprehensive phenotypic profiles and facilitates real-time monitoring of microenvironmental changes. This multi-source approach provides a robust data foundation for precision cultivation, early disease warning, and resource regulation [149–151].

Simultaneously, improving model interpretability and user accessibility is essential to building user trust and ensuring widespread adoption. Attention visualization, saliency map generation, and other explainability techniques can make model predictions more understandable and verifiable [23,72]. In addition, the development of graphical user interfaces tailored to farmers' operational habits can lower the technical barrier and significantly improve system usability in real-world agricultural contexts.

On the system integration front, the synergy between deep learning and intelligent agricultural machinery will be central to achieving field-level automation. Embedding vision-based recognition systems into UGVs or UAVs to form a closed-loop workflow—from perception and decision-making to control—will enable coordinated air–ground precision operations and elevate both the intelligence and efficiency of field management.

Moreover, deep learning is playing an increasingly vital role in promoting sustainable agriculture. When combined with precision agriculture strategies, deep models can facilitate quantitative pesticide spraying, water-efficient irrigation, weeds control, and intelligent fertilization, thereby safeguarding yield while reducing resource waste and environmental impact [152–154]. Furthermore, coupling crop–environment–management behavior through integrated modeling can enhance the agricultural system's responsiveness and adaptability to climate change, ultimately improving agroecological resilience.

Finally, the integration of digital twin technology with synthetic simulation data presents a transformative solution for agricultural AI training. By constructing a virtual twin environment for soybean cultivation and generating high-quality synthetic imagery via computer graphics, in conjunction with Sim-to-Real transfer learning frameworks, it becomes possible to significantly reduce dependence on real-world samples. This approach enhances model generalizability and robustness under real-world conditions, accelerating the practical and scalable deployment of deep learning technologies in agricultural production [155].

Among the numerous models and strategies reviewed, certain approaches have demonstrated particularly strong results in enhancing soybean production. For instance,

the SoyaTrans model, built on the Swin Transformer architecture, achieved up to 94% accuracy in disease classification, showing high potential for early disease management. MSAFNet, which integrates attention mechanisms and multi-scale feature fusion, delivered high precision in drought stress recognition, contributing to improved irrigation planning. Additionally, YOLOv8-based systems have proven highly effective in real-time pod and pest detection, supporting both mechanical operations and yield estimation. These successes suggest that models emphasizing lightweight design, attention modules, and multimodal integration offer the most practical and accurate solutions in real-world soybean farming environments.

7. Conclusions

This review concludes that deep learning has demonstrated significant potential in addressing various challenges across the soybean production chain, from early-stage perception to end-stage decision-making. While considerable progress has been made in areas such as image-based classification, segmentation, and object detection, practical implementation still faces barriers related to data quality, model generalization, real-time deployment, and reproducibility. Moreover, the complex and dynamic nature of agricultural environments requires further advancements in model robustness and adaptive capability. Future research should prioritize the development of unified evaluation benchmarks, the integration of domain knowledge, and the adoption of emerging paradigms such as reinforcement learning and self-supervised learning. Ultimately, the synergy between methodological innovation and system-level collaboration is expected to accelerate the adoption of deep learning in real-world soybean production and agricultural intelligence at large.

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